

# A Study on Spectral Super-resolution of Hyperspectral Imagery based on Redundant Dictionary

Ying Wu<sup>\*1</sup>, Suyu Wang<sup>2</sup>, Yibin Hou<sup>3</sup>

School of Software Engineering, Beijing University of Technology, Beijing, China

<sup>\*1</sup>wylemmon@163.com; <sup>2</sup>suyuwang@bjut.edu.cn; <sup>3</sup>yhous@bjut.edu.cn

## Abstract

With the wide application of hyperspectral imagery, the resolution required is higher and higher. Without increasing the equipment cost, a spectral super-resolution method based on redundant dictionary is presented in this paper to improve the spectral resolution of hyperspectral imagery. The redundant dictionary based over-complete signal sparse decomposition theory is applied to the super resolution of hyperspectral imagery. By sparse decomposing of the spectrum curve corresponding to each pixel along the direction of spectral dimension, super-resolution is applied to the complete spectral curve of each pixel, which can ensure the consistency of their spectral characteristics during the process of super-resolution restoration, while the spectral resolution of the hyperspectral imagery is improved effectively.

## Keywords

*Hyperspectral Imagery; Sparse Decomposition; Redundant Dictionary; Super-resolution Restoration*

## Introduction

Hyperspectral imagery is a two-dimensional image group obtained when the multi-spectrally imaging spectrometer images on the same surface feature. It comprises tens to hundreds of consecutive and segmental spectral information, and it has a high spectral resolution (Liguo Wang, Chunhui Zhao, 2014). With the improved spectral resolution, it is accompanied by the increase of the cost of the equipment when obtaining the hyperspectral imagery. Therefore, under conditions of constant cost, the super-resolution restoration method which is using the mathematical methods and signal theory to obtain the high-resolution images has become the hot topic in the field of improving image resolution.

The super-resolution image restoration is a method that rebuilds a high-resolution image at the same scene through a piece or pieces of low-resolution

images and removes noise in the original low-resolution image (Xuefeng Yang, 2011). For hyperspectral imagery, super-resolution algorithm is designed for two kinds of resolutions—spatial resolution and spectral resolution. There are extensive studies on the spatial resolution in recent times, and relatively less attention to spectral ones. At present, the non-mean interpolation method is the most intuitive way in the super-resolution restoration study on the spectral super-resolution of hyperspectral imagery. But due to ignoring the error introduced by the interpolation process, the non-mean interpolation method cannot guarantee the optimum of the entire restoration algorithm (Xuefen Wang, Yi Yang, Jian Cui, 2011).

In the analysis of hyperspectral imagery, Chunmei Zhang et al (2006) noted that, in the over-complete decomposition of the image, the design of atoms to form a redundant dictionary should reflect the important characteristics of the original image as possible. Adam S. Charles (2011) establishes a comprehensive feature information dictionary using the method which training the actual hyperspectral imagery pixel based on unsupervised learning to build redundant dictionary. This method could get more and more effective feature information. The above results show that the sparse representation based on redundant dictionary could describe the feature information in hyperspectral imagery better. For this reason, a super-resolution restoration method based on redundant dictionary is presented in this paper. In this method, the establishment of the high and low resolution redundant dictionary is the core. The method can be summarized as follows. First, establish the training sample library with spectral curve of high and low resolution corresponding pixel. Then, learn to get a pair of over-complete low and high resolution redundant dictionary by constraining the high and

low resolution pixels with the same coefficient. In the restoration process, for each pixel in the hyperspectral imagery of low resolution input, sparse decompose the image based on low resolution redundant dictionary to get a set of sparse coefficient firstly. Then reconstruct the high-resolution hyperspectral imagery using the high resolution dictionary and the obtained sparse coefficient. Redundant dictionary application to hyperspectral imagery spectral super-resolution recovery can reduce the overall amount of computation, and ensure the consistent spectral characteristics in recovery process, effectively improving the spectral resolution of the hyperspectral imagery and the descriptive power of spectral characteristics.

### Spares Decomposition for Hyperspectral Imagery

The sparse representation of signals can effectively extract the signal characteristics. It is useful for the subsequent processing, and also can reduce signal processing cost in essence. The traditional signal representation is the signal carried out based on a group or a plurality of orthogonal basis, such as the classical Fourier transform, wavelet transform etc. But because the orthogonal decomposition has certain limitations, and the composition of signal itself can be complex, the effect will be even worse for the signal of frequency changing in a wide range. Different from the signal traditional orthogonal basis theory, the over-complete sparse decomposition theory uses the over-complete redundant function system instead of orthogonal basis functions. The over-complete redundant function system is also called the redundant dictionary. It is without any restriction in structure, and it can be composed of different basis function. Signal sparse decomposition is a process of founding  $m$  atoms with the optimal linear combination to represent the signal. The method based on redundant dictionary provides a variety of basis function and it can adaptively select basis function suitable for signal decomposition based on the characteristics of the signal during the signal expansion process, so we can get more and better sparse representation results. And the method is more focused on information rather than data when describing the signal, thus, some important natural characteristic of the original signal is often able to capture which the traditional methods cannot get.

As a kind of the multi-dimensional data, the

hyperspectral imagery can also be sparse coding through the redundant dictionary. The hyperspectral imagery can accurately describe each pixel spectral features using a plurality of continuous band, and the pixel in the similar surface area has similar spectral curve characteristic. It is resulted by the dispersion and aliasing of the spectral curves of various types of surface features in the area covered by the pixel. As shown in Fig. 1, each blue line is shown as a spectral vector of a pixel, the continuous pixel distribution form the smooth vector curve, each red line represents the spectrum vector of some definite kind of materials. Although the spectral vector of pixel and endmember shown in the picture is just the special case of three-dimensional, in actual situation, each spectral vector is multidimensional form in hyperplanes. But looking the spectral characteristics as a whole, you still can feel that it is more natural and reasonable to sparsely decompose the pixel data.

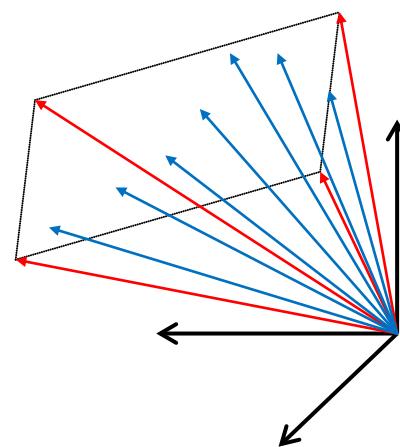


FIG. 1 SCHEMATIC DIAGRAM OF SPECTRAL VECTOR OF PIXEL AND ENDMEMBER

The technique of hyperspectral imagery sparse decomposition based on redundant dictionary can sparsely code the images from the perspective of looking the spectral curve as a whole. This technique can effectively maintain the spectral characteristics consistent and accurately sparse reconstruct the original data. Many problems faced by the super-resolution restoration of hyperspectral imagery are from how to ensure not to damage the spectrum characteristics.

### Hyperspectral Imagery Super-resolution Restoration

Establish redundant dictionary for each group of features by learning and training method. Select the most representative spectral characteristic curve in this

class of objects as the atoms for the description of any spectral curve, and to achieve efficient sparse decomposition of the hyperspectral imagery. The current mainstream method is to form the training based on learning, generating atoms in dictionary by training the data itself, for example, the best direction method (MOD), generalized PCA method, K-SVD method, and sparse dictionary learning methods. In these methods, K-SVD method is the most common method currently (Mianzheng Lu, 2012; Jie Ren, 2013; R. Rubinstein, 2010; Rim Walha, 2013). The K-SVD method is adopted in this paper to train the redundant dictionary.

First, for each type of typical objects, select a group hyperspectral imagery which contains enough spectral information as the training sample, determining the dictionary which can describe the spectral characteristics effectively by learning and training method. Take  $X = [x_1, x_2 \dots x_N]$  as the training sample data,  $\Lambda = [a_1, a_2 \dots a_N]$  as Sparse matrix of sparse decomposition. So the design process of the dictionary is the process of resolving the constrained optimization problems of the Eq. 1.

$$\arg \min_{D, \Lambda} \|X - D\Lambda\|_F^2, \text{ s.t. } \forall i, \|a_i\|_0 \leq T \quad (1)$$

where  $a_i$  presents the column  $i$  of  $\Lambda$ ,  $\|\Lambda\|_F$  presents the Frobenius norm, that is  $\|\Lambda\|_F = \sqrt{\sum_{ij} A_{ij}^2}$ .

The optimization process is the process of renewal of the coefficient and the dictionary. It means looking for a group of the most representative spectral characteristics on the objects to make each training sample achieve optimal sparse decomposition based on the dictionary and at the same time any hyperspectral imagery obtained by the same remote sensing could achieve good sparse decomposition based on the dictionary. This paper uses K-SVD algorithm to solve the optimization problem.

Based on the redundant dictionary design method about object classes, we study a constraint learning

design method of the high and low resolution redundant dictionary. First, for each type of typical object, selecting a group of hyperspectral imagery contains enough information of the high resolution spectral features. Then selecting part band as the low resolution image. Define the high resolution pixels in the training sample as  $X_h$ , corresponding to the low resolution pixels as  $X_l$ , so the corresponding resolution dictionary can be obtained by minimizing the following objective equation.

$$\{D_h^*, D_l^*, \Lambda^*\} = \arg \min_{D_h, D_l, \Lambda} \|x_h - D_h \Lambda\|_2^2 + \|x_l - D_l \Lambda\|_2^2 + \lambda \|\Lambda\|_1 \quad (2)$$

In the Eq. 2,  $\Lambda$  presents the vector composed of sparse coefficient  $a$ .  $D_h^*$  and  $D_l^*$  are the optimal high and low resolution redundant dictionary obtained by training.  $\lambda \|\Lambda\|_1$  is the regularization form problem for solving the optimization problem. In order to ensure that it could use the decomposition coefficients of the low resolution pixels and high resolution redundant dictionary to rebuild the high resolution hyperspectral imagery, we need to keep the decomposition coefficient of high resolution pixel decomposed on the high resolution dictionary consistent with the decomposition coefficient of low resolution pixel decomposed on the low resolution dictionary.

After building the high and low resolution redundant dictionaries, for the any pixel  $x_l^i$  in the low resolution hyperspectral imagery, we could obtain the sparse representation coefficients through the Eq. 3.

$$a^* = \arg \min_a \|x_l^i - D_l a\|_2^2 + \lambda \|a\|_1 \quad (3)$$

Accordingly, the pixel of high resolution hyperspectral image  $x_h^i$  could be obtained by the Eq. 4.

$$x_h^i = D_h a^* \quad (4)$$

Through the detailed description of the process of the super resolution restoration on the hyperspectral imagery spectral above, the whole process can be simply expressed as what the Fig. 2 shows.

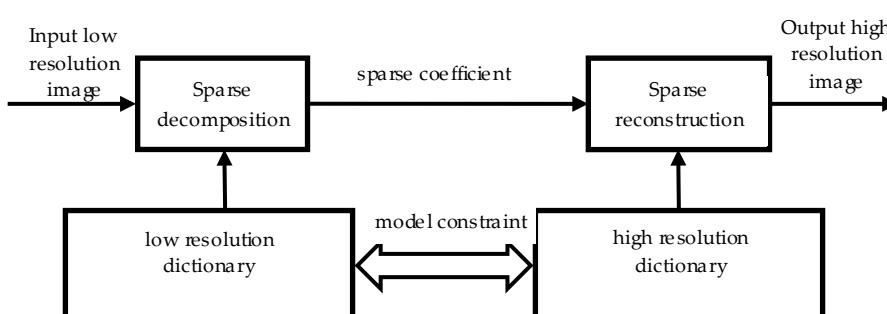


FIG. 2 THE PROCESS OF SPECTRAL SUPER-RESOLUTIONG OF HYPERSPECTRAL IMAGERY BASED ON REDUNDANT DICTIONARY

## Experimental Results

The hyperspectral imagery materials are all got from the hyperspectral remote sensing OMIS. We select the three pieces of hyperspectral image River1, River2, River3 as the experimental data. Each piece is composed of 128 bands, 512 \* 512 pixels. Select River2 as the dictionary training sample set, because it contains a greater variety of objects, and it also contains most objects in River2 and River3. So the information in River2 is more comprehensive and more general.

We have two ways to evaluate the result of the super-resolution of hyperspectral imagery in this work. One is the objective value comparison, the other is the subjective judgment. They all compare with the original high-resolution hyperspectral images and the interpolation reconstruction hyperspectral images. We use the PSNR (Peak Signal to Noise Ratio) as the objective value evaluation criteria.

The experiment results show that the hyperspectral imagery reconstructed by this method proposed in this paper is closer to the original hyperspectral imagery than the interpolation method, and the PSNR value is higher than the interpolation method, the specific value is shown in Table 1.

TABLE 1 THE PSNR VALUE COMPARE BETWEEN RECONSTRUCTION IMAGES AND INTERPOLATION IMAGES OF RIVER1 AND RIVER3

Number	River1 reconstruction	River1 interpolation	River3 reconstruction	River3 interpolation
Whole band	38.242919	33.478417	41.651154	32.185499

It is obviously that the data in Table 1 shown this method improving the spectral resolution of hyperspectral imagery more effectively.

## Conclusions

The experimental results show that the super resolution restoration method proposed in this paper can effectively improve the spectral resolution of hyperspectral imagery. According to the information collected from the same remote sensor at the same area, the high spectral resolution hyperspectral imagery can be reconstructed by the low spectral resolution hyperspectral imagery, which could reduce the equipment cost required in the acquisition of hyperspectral imagery.

The successful application of this method has laid a good foundation for the later research. Furthermore,

we will research how to improve the spatial resolution and spectral resolution of hyperspectral imagery at the same time. The restored image obtained by the method proposed in this paper still has a gap with the original in some bands. In future research, we will optimize the training process of the dictionary and the restored map can improve image quality by some methods, to achieve better results.

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**Wu Ying** was born in Beijing, China in 1989. She received the B.E. degree in software engineering from China University of Geosciences in 2007 and the M.E. degree in software engineering from Beijing University of Technology in 2014, Beijing, China.

She studied in school of software engineering of Beijing University of Technology. Her research interests include image and video processing, sparse representation and compressive sensing.

**Wang Suyu** received the B.E. degree in Hebei University, Hebei, China in 1999, the M.E. degree in Sichuan University, Sichuan, China in 2002, the Sc.D. degree in Beijing University of Technology, Beijing, China in 2008, and has the post-doctoral research in Beijing University of Technology from 2008 to 2010. She has joint research and undertaken the Research Associate work in department of electronic and

information engineering of Hong Kong Polytechnic University.

She participated in more than 10 research projects, published more than 30 papers, participated in two patents and 4 software copyrights. Her research interests include image and video processing, embedded systems and so on.

**Hou Yibin** received the M.E. degree in department of computer science from Xi'an Jiaotong University, Xi'an, China, the Sc.D. degree in department of electrical engineering from EINDHOVEN University of Technology, Holland.

He was a professor of computer science, computer science doctoral tutor, vice president of engineering studies, director of the computer institute in Xi'an Jiaotong University from 1990 to 2002, dean of School of Software in Beijing University of Technology, director of embedded computing institute, director of software and networking systems engineering technology research center, Beijing since 2002. He published more than 100 papers, a scholarly monograph, 5 invention patents and a science film. Her research interests include software engineering, embedded computing, networking technology and applications.